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Contextual Emotion Detection of E-Learners for Recommendation System

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Abstract : In the recent pandemic times, there was an impactful transformation in imparting education which required everyone to become online learners. There has been an exponential growth in the number of e-learners attending classes online and taking MOOCs courses. This has opened an avenue for research to analyze the emotion of e-learners through reviews of students to evaluate the learning outcomes and performance of the course. Most challenging task is to find the exact pulse of the e-learners' emotions from the huge data of the e-learners reviews. The reviews on all online platforms are mostly textual and this qualitative data needs to be quantified for analysis. There is a necessity to propose contextual emotion detection of e-learners by extracting the relevant information which can be correlated to the performance of the course on e-learning platform. Further, it can be a recommendation system to the aspiring e-learners to make decision based on the satisfaction index of previous e-learners. This paper leverages deep learning techniques to train various models for academic emotion detection using dataset E-Learners Academic Reviews (ELAR) prepared from online textual feedback of e-learners and MOOCs course reviews. The Bidirectional Encoder Representations from Transformers (BERT) transfer learning model used to detect the emotions outperformed the other models. This proposed method using ELAR dataset is a novel approach to identify the right emotion of e-learners from the course reviews available on e-learning platform. The results were discussed with a benchmark of ISEAR (International Survey on Emotion Antecedents and Reactions) and GoEmotion Dataset.

Keywords : Academic emotions; Digital natives; Deep learning; E-learners; Textual emotions

1. Introduction

Generation-Z (Gen Z) characterize the students born after 1997 who have experienced internet in their early childhood days. There is a complete transformation of the way they look at education and gather knowledge. For this Gen Z the teaching learning process is redefined for active engagement. They are proficient with electronic gadgets ubiquitously. They enjoy learning in blended synchronous and asynchronous mode of course delivery Yu (2019).

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These digital natives are comfortable to network and communicate actively on social media. Perception of education is all about choosing the course or right content available on a click through search engines (Seemiller et al., 2019). The e-learners can pick the courses for learning preference or of choice to fix academic road map.

In the era of automation most of the devices, products, machines and processes have to integrate affective computing feature. These automated e-learning platforms need to be developed taking into consideration the emotions of users and empathize for appropriate responses. The current e-learning platform incorporates affective computing during design for better user experience. Journal writing, self-reflection reports, peer review and feedback enable them to assess their metacognitive skills (Garcia-Garcia et al., 2018). Text mining of information from these indirect assessment tools can give the emotions of the participating learners. Feature engineering the emotions from unstructured data is challenging and requires right model selection, dataset and training

The current research of improving e-learning platform for engaging the e-learners by analyzing the data of e-learners experience for personalized academic progress tracking and suggestions is growing exponentially (Zhou & Tao, 2020). The need of hour is to develop e-learning courses and MOOCs with emotional connect and context as key aspect for achieving the desired performance. Sentiment analysis actually talks about whether the perception is positive, negative or neutral. is associated with classifying the reviews as positive and negative. It is associated with classifying the reviews in binary state. Whereas emotion analysis talks different levels of feeling which are fuzzy in nature. These feelings are obvious and vary from person to person. These wide range of emotions need to considered when detecting and analyzing the participation of e-learners. Emotion analysis can give precise mood and attitude of e-learners.

Digital natives take into consideration reviews available on social networks before making decisions (Evans & Robertson, 2020). The digital natives as e-learners are keen to give reviews of the online course taken so as to help the aspirants taking the course getting the first-hand information in making the right choice. Thus, it is required to analyze the quality of online courses by detecting the emotions from the large number of reviews and star ratings submitted by e-learners. The previous work of emotion detection used classification-based machine learning algorithm Support Vector Machines (SVM) and Naive Bayes (NB) to classify and identify emotion from a sentence. These models were good for text classification problems. Deep learning techniques can be used to extract emotions providing improved performance over traditional machine learning models. In this paper, we propose emotion detection from contextual information by training deep learning models (Li et al., 2022). Deep Learning networks are made of input, hidden and output layer. The neurons in them are densely connected to each other and they give the dimensionality of the output vector from the preceding hidden layer so that the model can easily detect the emotion from the input reviews of the data from e-learning platform for which the model is trained. The deep learning models require big data and are hence computationally expensive which take a lot of time to train the model but they offer great performance for feature engineering the unstructured data (Acheampong et al., 2020).

2. Background and Related Work

Sentiment analysis from long had been a popular tool for massive open online course (MOOC) instructors to gather the sentiment of learners based on their participation in discussion forums. The content delivered by instructors was reviewed by investigating discussion forums, chats (Coetzee et al., 2014) which states that MOOC learners' experiences were not affected by instructor suggesting or intervening in discussion going on with the peers online. The study did not include analysis of learner's sentiments in case instructors regularly provide individual feedback. The understanding of learners to interpret the tools, MOOC platform and ways to navigate to different assessment tools and participation in discussion forums was studied. Instructors monitoring student performance were surveyed and data mining for quantitative analysis was done to provide visualizations.

The impact of sentiment on attrition over time (Rabbany et al., 2013) was studied in order to monitor learners' opinions towards the course. In this paper Survival analysis statistical modeling technique was used to model the effect of various indicator and dependent variables at any given time. The effect of certain language behaviors and sentiment were modeled and probability that a student does not participate the forum participation on the next time point was analyzed to gather sentiment polarity.

Emotion detection from text was done for the news headlines by (Strapparava & Mihalcea, 2008) basically to classify as positive news or negative news. The dataset SemEval 2007 was developed from news websites and as headlines consists of few words it was suitable to identify positive or negative sentiment from the keywords. In this case knowledge based and corpus-based techniques were used to label the mood of the blogposts.

Learning analytics tool mentioned in paper used Machine learning techniques for identifying the students at risk of dropout from the course (Kuzilek et al., 2017). The predictive model was designed considering demographic data and learners' interactions on the Virtual Learning Environment (VLE) system using k Nearest Neighbors (k-NN). The students' progress was tracked weekly based on activities and demographic data using machine learning algorithm based predictive model was investigated in this paper. The data was captured from the eleven ongoing courses with various correlation of fields related to age, gender, previous qualification. The predictive models proved to very useful to the course tutors and course teams.

A model for prediction using learning analytics in MOOCs was done for finding the student retention in a course using an vector-based support vector machine (RTV-SVM). This model was used for notifying them well in advance about their progress in order to increase retention rate, improve the learning experience (Khalil & Ebner, 2016). Two courses were used to analyze the success rate depending on the weights assigned to each activity as per their adequate significance.

Another deep learning Natural language processing (NLP) techniques were proposed by Guo, (2022) to enhance the performance of learning based on emotion classifier. The technique used extracts of syntactic and semantic features of text for the purpose of analysis. The deep learning assisted semantic text analysis (DLSTA) model detected the emotional state by analyzing the written text using word embedding's method from questionnaire. It also emphasized the benefits of detection and data sources used for the process from user perspective and further classifying them into seven different emotional labels.

Feature extraction of unstructured text data required data cleaning and preprocessing before converting text into numerical value. The common feature transform techniques used for text preprocessing was Word to vector. Word2Vec was a predictive deep learning model to compute and to generate continuous vector numeric representations of words (Liang et al., 2017). This feature was used to capture vectorized quantitative information. It was an unsupervised model which created a vector space of text. By specifying the size of the word embedding vectors the dimensionality of dense vector space was set. word2vec used the Continuous bag of words (CBOW).

3. Dataset

The biggest challenge was to find labeled dataset of academic reviews. As most standard dataset of reviews found were business, product and service based. So, the trained academic reviews dataset used from e-learning and MOOCs platform were required for accurate emotion detection of e-learner during the course. There was a need for the dataset of academic emotions collected from e-learner's reviews, discussion forums and annotating the emotions.

There could not be a direct comparison with benchmark emotion dataset as they had samples of social media chats, blogs and general views. The language used on social networking sites could not be base for academic emotion detection. In this paper major attention was focused on course reviews of e-learners. The course reviews were always academically driven words which reflect emotion during learning process. The most popular emotion dataset used by researchers for emotion analysis were ISEAR (International Survey on Emotion Antecedents and Reactions) dataset which consisted of seven emotions each by close to 3000 respondents in 37 countries on all 5 continents. This dataset was prepared by group of psychologists all over the world. Student participated and recorded the situations in which they had experienced 7 major emotions namely joy, fear, anger, sadness, disgust, shame, and guilt (Adoma et al., 2020).

EmoContex dataset contained 4 classes of emotions extracted from user interaction with a conversational agent (Chatterjee et al., 2019). Recurrent neural networks using deep learning and hierarchical model could be helpful in contextual emotion detection (Yan et al., 2021). GoEmotions

English Reddit comments, labeled for 27 emotion categories and BERT based model achieves an average F1-score of 0.46 (Demszky et al., 2020). This emotion dataset available in general did not include the student's emotions during the learning process. This in turn could not accurately help in identifying the emotions of e-learners on MOOCs platform if it was train by the generalized available emotion dataset.

The ELAR Academic emotion dataset was prepared by scrapping reviews from various e-learning platforms. They were the reviews and feedback shared by the e-learners on e-learning platforms, MOOCs comprised of keywords frequently used by e-learners. The e-learners review was also collected by star or number rating from 1 to 5 rating the course. The dataset size was 80940, 16188 reviews were scrapped for each academic emotion class. These emotions were mapped to rating given by e-learners on a scale of 1 to 5. Labeling the academic emotions was done on basis of rating and keyword spotting. This ELAR dataset can be used in many research areas related to smart education where the student engagement, satisfaction and concentration in online class has to be improved. ELAR is a balanced dataset wherein all the 5 academic emotions labels have equal number of reviews.

Academic Emotions of e-learners

In current scenario there is a need for specifying and analyzing academic emotions. Academic emotions of E-learners majorly experienced during the learning process identified are as follows:

a. Excitement – Active participation strategies, challenging critical and creativity of e-learners on the e-learning platform creates excitement. Empowering and encouraging the e-learners during online learning motivates to push towards consistent learning and achieve all the learning outcomes. E-skilling on these platforms and experiential learning creates an excitement in e-learners. Reward system, innovative teaching pedagogy during class, gaming, animation, real-time application analogy or pear assessment makes them confident and excited (Smidt et al., 2016). The linear learning trajectory of the e-learners reflects excitement. There is a stronger chance of e-learner enrolling for the next course on e-learning platform. Dopamine levels are high when the e-learners are excited during their learning process (Tzafilkou et al., 2021). It is mapped to star rating and numerical rating of e-learners received as 5 on scale.

b. Happy – Encouraging interactive participation techniques during the course and in assessment makes the online learners happy. The course content delivery is significant in retaining the students. Suggestions during quiz assessment about referring a topic, quiz indicators embedded in lecture, multiple chance to take up the assessment quiz before the deadline are the multiple parameters which affect the happy state of e-learner. Feedback after every module completion about the complexity of topic, quiz questions gives the e-learners a sense of responsibility for contributing towards course upgrading. E-learners will happily take up the suggestion of next course in continuation. It is mapped to star rating and numerical rating of e-learners received as 4 on scale.

c. Satisfied - Online learning require being self-driven and self-directed to complete the course timely. E-learners can sometimes feel lonely and don't find the motivation to complete it at a fast pace. Although some participants will be happy as the deadlines can be readjusted and is a self paced way of learning. It is mapped to star rating and numerical rating of e-learners received as 3 on scale.

d. Not Satisfied – This emotion is usually due to poor instructional design. The key components of instructional design target audience, teaching pedagogy, learning objectives, formative and summative assessment methods and instructional strategies all attribute towards unsatisfied e-learners. This leads to course dropouts due to lack in engaging the course. E-learners experience dissatisfaction and are not able to meet their learning objectives. Thus, e-learners, might be losing interest, and learning gets affected due to lack of emotional interaction with the instructor instant query resolution. E-learner's emotions during the course enhance the learning experience (Khalfallah & Ben Hadj Slama, 2018). It is mapped to star rating and numerical rating of e-learners received as 2 on scale.

e. Frustration - Frustration appears in e-learners when they are not able to locate important resources during the assessment and when the expected reward which they were aiming for starts slipping out of hands. Frustration arises in e-learners when they perceive that their learning outcome will not be fulfilled and is likely to increase when they are not able to complete the tasks due to lack of understanding. This emotion in e-learners is due to fear of losing, lack of motivation due to the ambiguity in instructions, course not organized on the platform, difficulty in tracking the important notification, announcements and progress. It is mapped to star rating and numerical rating of e-learners received as 1 on scale.

4. Methodology

Deep learning algorithms were used to extract contextual features using hidden layers. There were various deep learning techniques used for text classification, recognition, summarization and information analysis. The Deep learning techniques implemented for textual emotion detection from course reviews are shown in Fig. 1.

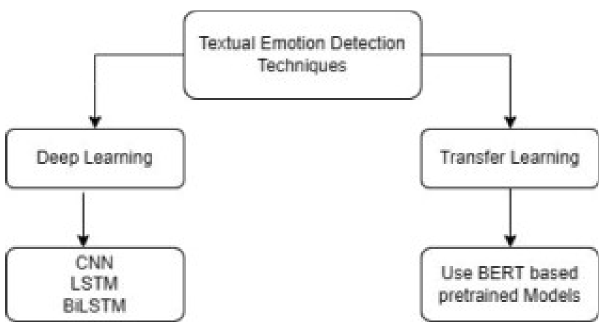

Fig. 1 : Textual Emotion Detection Techniques

The course reviews and feedbacks of e-learners available on e-learning platform were large textual data. These were analyzed for developing good recommendation system to prospective e-learners. Most of the course reviews available in star rating were rated on a scale of 1 to 5. These were annotated to academic emotion as per the sentiment of the reviews. Text preprocessing was performed on input available by removing slang, symbols, alphanumeric character, email ID, vowels and stop words. Text preprocessing was done by using the multiple regular expression technique. In deep learning feature extracting was done by hidden layers.

Emotion Detection using deep learning Models was used to extract academic emotions from the huge course reviews and feedback of the e-learners. The feature extraction in deep learning was done using convolution neural network (CNN) word2Vec, Long short-term memory (LSTM), Bidirectional Long short-term memory (BiLSTM) and Transfer learning based BERT model (Wang et al., 2015). The proposed deep learning models trained on E-Learners Academic Reviews (ELAR) Academic emotion dataset shown in fig 2. These model performances were compared and tested for the real-time reviews to validate the system. The experimentation in this work were implemented in Python,

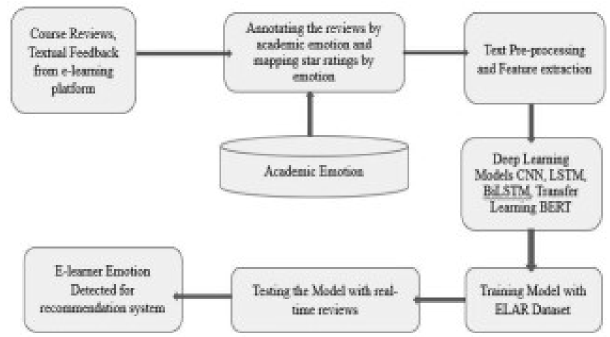

Fig. 2: Flow diagram for text emotion detection

Google Colab platform using the Keras library which was based on the TensorFlow deep learning framework. The model was trained by splitting dataset, 80% for training and 20% for testing. The real-time reviews were given to the trained model and output academic emotion percentage mapping were tested of the learner's perception about the course.

The deep neural network used to measure the performance were configured as follows:

a. Convolutional Neural Networks (CNN) was configured for 3 hidden layers, Convolutional Layer, Pooling Layer, and Fully-Connected Layer. The layered architecture consisted of 128, 128 and 256 neurons. The output layer was a dense layer using the SoftMax activation function to output a probability prediction. (Xu et al., 2019)

b. Long short-term memory (LSTM) introduced gates to avoid information loss in long sequences. They were suitable for sequential data (Pogiatzis & Samakovitis, 2020). In this case configuration considered were 5 layers (LSTM, Dropout, Batch Normalization, Flatten, Dense), running the model at 128 batch size, 25 epochs final Validation accuracy of 84.5% achieved.

c. Bidirectional LSTM (BiLSTM) layer learned bidirectional long-term dependencies and calculated the input sequence from the backward direction to a forward hidden sequence and again forward to backward hidden sequence of data. These dependencies were useful when the network learned from the complete sequence. Bi-LSTM here offers a better accuracy as compared to LSTM model with complex layers to filter and predict better than LSTM. Total of 6 layers (Bi-LSTM, Conv1D, Global MaxPool1D, Dense, Dropout, Dense) were trained with an epoch of 25 and the final Validation accuracy is 85.6%.

d. Bidirectional Encoder Representations from Transformers (BERT) framework learned contextual relations between words in a text. It included bidirectional mechanism with an encoder that read the text input and a decoder that produced a prediction for the task. It generated e-learner's contextual academic language model which was bidirectional and considered pre and post words in a text (Li et.al.,2020). The model was trained using pre-trained BERT uncased transfer learning. The parameters used in implementation were hidden layer activation RELU, output activation layer sigmoid, Adam optimizer and learning-rate of 5e-05.

5. Performance Analysis

Accuracy and precision were used for performance metrics to compare performance of the deep learning models implemented. F1 score gave a mean of precision and recall which was calculated considering false negatives and false positive. Accuracy gave a measure of true negatives and true positives. Table 1 shows the comparison of implemented models. The bidirectional architecture approach of BERT gave best accuracy of 92.2% compared to other algorithms.

Table 1 : Comparison of performance measures of deep learning model on elar dataset

Deep Learning Model	F1 Score	Accuracy
CNN	0.57	72.83%
LSTM	0.84	83.8%
BiLSTM	0.86	85.6%
Transfer Learning Based BERT	**0.89**	**92.2%**

6. Results and Discussion

The results of transfer learning-based BERT model gave the percentage of correlation of all the academic emotions. Thus, from the results it was analyzed whether the review was tending towards positive or negative review. The test results of BERT model input were taken from the online learners and the results were analyzed. BERT transfer learning-based model predicted the results by considering the pre and post context words from the input. It was concluded that transfer learning-based BERT model gave best accuracy.

To test the BERT model prediction results, some of the course reviews of e-learners were taken as input and the output results of the model in terms of percentage of each academic emotion were obtained.

1. Input the review- running fast coping up

frustrated	17.040861
not satisfied	33.089035
satisfied	86.62825
happy	81.61365
excited	20.434563

2. Input the review- instructor really described it well and fell in love with the course

frustrated	1.801508
not satisfied	30.990631
satisfied	14.2506075
happy	33.74712
excited	98.60218

3. Input the review- This is the worst course of my life

frustrated	6.4122505
not satisfied	99.812584
satisfied	31.435295
happy	57.0481
excited	49.593277

4. Input the review- very unhappy, waste of time

frustrated	99.52587
not satisfied	79.3993
satisfied	65.91313
happy	43.443203
excited	6.6544986

From the above examples, in case 1 it showed that the e-learner was satisfied and happy, whereas in case 2 it was found to be a completely excited e-learner. In case 3, the e-learner was not satisfied with the course and in case 4, the results reflected that the e-learner was frustrated. The recommendation model was effective as it predicted precisely the e-learners emotion about a course from a large number of reviews.

7. Conclusion

This paper modeled the transfer learning BERT academic emotion model for the identification of human emotions using course reviews and textual feedback. There had been an enormous growth in the number of e-learners for online classes and MOOCs courses and exact pulse of the e-learner's emotions from the huge data of the e-learner's reviews was found out as its need. The textual reviews were taken from online platforms were quantified for purpose of analysis. The relevant information was extracted to detect the contextual emotion of e-learners to correlate to the performance of the course on e-learning platform. The BERT model accelerated the emotion detection process of course review input in one go compared to CNN based models which tokenized each word. It was observed from the results obtained that deep learning BERT model which feature engineered through hidden layers the emotion of e-learners was effective for predicting the e-learner's academic emotion with high accuracy. It proved that transformer based deep neural network outperformed CNN, LSTM and BiLSTM in natural language processing due to its bidirectional architecture.

The results obtained can be correlated to assist the trainers for corrective measures in course delivery based on the emotions of the e-learners. Further the emotion of e-learner obtained through the trained model helps the enthusiastic learner explore the suggestion given by model to choose the best e-learning platform. It will also further help to gather the sentiment of e-learner and recommend right courses to prospective learners. The academic emotion dataset (ELAR) trained model is specially designed for academics incorporated in learning management system provides right emotion of e-learner to the university hosting the course.

Further the work can be extended to quantize the satisfaction Index of e-learners on any e-learning platform. It can also be correlated to measure of attentiveness, alertness and engagement of e-learners. This in turn can predict the student performance and overall course popularity. The notifications or pop-up messages can improve the e-learner engagement in class and a career path can be recommended. Multimodal approach with help of facial expressions in case of proctored learning, audio signals recorded for a particular topic or feedback recorded of the e-learners can make the emotion detection more robust. It can enhance the experience on e-learning platform by constructively implementing feedback for improving the engagement during online learning.

Declarations

Dataset is prepared from the text reviews and textual feedback received from students from our institution and from various MOOCs platform. Due to privacy and ethical concerns, cannot share the dataset at present but after removing the identity and cleaning will be made available on reasonable request.

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